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RESEARCH ARTICLE

Prediction of municipal solid waste generation using artificial neural network approach enhanced by structural break analysis

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Abstract This paper presents the development of a general regression neural network (GRNN) model for the prediction of annual municipal solid waste (MSW) generation at the national level for 44 countries of different size, population and economic development level. Proper modelling of MSW generation is essential for the planning of MSW management system as well as for the simulation of various environmental impact scenarios. The main objective of this work was to examine the potential influence of economy crisis (global or local) on the forecast of MSW generation obtained by the GRNN model. The existence of the so-called structural breaks that occur because of the economic crisis in the studied period (2000–2012) for each country was determined and confirmed using the Chow test and Quandt–Andrews test. Two GRNN models, one which did not take into account the influence of the economic crisis (GRNN) and another one which did (SB-GRNN), were developed. The novelty of the applied method is that it uses broadly available social, economic and demographic indicators and indicators of sustainability, together with GRNN and structural break testing for the prediction of MSW generation at the national level. The obtained results demonstrate that the SB-GRNN model provide more accurate predictions than the model which neglected structural breaks, with a mean absolute percentage error (MAPE) of 4.0 % compared to 6.7 % generated by the GRNN model. The proposed model enhanced with structural breaks can be a viable alternative for a more accurate prediction of MSW generation at the national level, especially for developing countries for which a lack of MSW data is notable.

Keywords MSW management · General regression neural network · Structural breaks

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Introduction

Anthropogenic activities are always associated with the production of waste to a greater or lesser extent; hence, appropriate management of municipal solid waste (MSW) is crucial for any community in order to prevent environmental pollution and to reduce the risk for public health. Planning and development of strategies for waste management greatly depend on the ability to accurately predict the amount of MSW (Daskalopoulos et al. 1998; Bandara et al. 2007; Noori et al. 2009).

The main drivers of progressive growth of the quantity of generated waste are the increase in population, economic growth, as well as changes in life style and consumption patterns. The connection between the level of economic development and the quantities of MSW generated has been particularly significant (Breede and Bloom 1995; Khajuria et al. 2011; Hoornweg and Bhada-Tata 2012).

In the overall theory of economy, it is well known that various significant events such as political or economic crisis, natural catastrophes, wars, etc. can cause major changes in the economy that can lead to large differences in various socio-economic parameters, including the amount of generated MSW, for a period before and after this change (Gujarati and

Porter 2009; Greene 2012). These differences in socio-economic parameters, which are referred to as structural breaks (Verbeek 2004), have been identified as a reason for a decrease of the accuracy of models based on economical parameters, e.g. the accuracy of the bankruptcy prediction model, under crisis conditions, dropped from 83.3 to 66.7 % or even lower (Sung et al. 1999). Although the impact of an economic crisis on the amount of MSW generated has still not been sufficiently studied, it can be assumed that significant changes in the economy are reflected in the generation of MSW (Inglezakis et al. 2012; Watson 2013).

Artificial neural networks (ANNs), among other regression methods, have been widely applied for the prediction of MSW generation (Noori et al. 2010; Ali Abdoli et al. 2011; Batinic et al. 2011; Antanasijević et al. 2013a; Shamshiry et al. 2014).

The modelling of solid waste generation on a weekly basis in Mashhad (Iran) was performed using back propagation (BP) ANN by Noori et al. (2010). Heuristic techniques and standard numerical optimization techniques have been used to optimize the network weights and bias in the BP ANN model. The reduction of the initial number of input variables (13) was performed using principal component analysis (7 inputs) and Gamma test (5 inputs), whereby these models have more effective results than the initial ANN model.

Also, the capability of multilayer perceptron (MLP) for modelling of long-term solid waste generation for the period of 2011–2032 in the city of Mashhad (Iran) was studied by Ali Abdoli et al. (2011). MLP is a type of feed forward ANN consisting of layers which are all fully connected and where neurons are represented by perceptrons with non-linear activation function. MLP utilizes back propagation as a supervised learning technique (Rosenblatt 1961; Rumelhart et al. 1986; Chau and Wu 2010). Population, household income and maximum temperature were indicated as significant factors for the generation of solid waste. Comparison between the results of ANN and multivariate regression model indicated that ANN approach had better performance in predicting the municipal solid waste generation.

An ANN model was used to determine the relation between the amount and composition of generated waste on one side with socio-economic indicators in ten municipalities of Serbia on the other (Batinic et al. 2011), with the average income, level of employment, age structure, educational level and housing conditions being used as socio-economic input indicators. Outputs were presented as six waste categories as follows: organic waste, paper, glass, metal, plastic and other waste. The model used projected socio-economic inputs for 2010–2026 to forecast the quantity and composition of waste.

In order to develop an ANN model for the prediction of annual MSW generation in European countries, two different architectures were evaluated: back propagation neural network (BPNN) and general regression neural network (GRNN; Antanasijević et al. 2013a). The gross domestic product (GDP), domestic material consumption (DMC) and resource productivity (RP) were used as input variables and municipal solid waste generation as output parameter, and data for 26 countries from the Eurostat database were used for the training and validation of the models. With both models (BNNN and GRNN) trained and tested using the same dataset, the model based on GRNN architecture achieved better results.

The prediction of the amount of solid waste in the tourist area of Langkawi Island, Malaysia during 2004–2009 was carried out using multiple regression analysis (MRA) and ANN (Shamshiry et al. 2014). Weekly data of solid waste generation were used as the output variable, while the fuel consumption, types of trucks and their trips and number of entrances to landfill were used as the input variables. Comparison between the final results showed that ANN has higher accuracy than regression analysis.

This paper describes the development of an ANN model enhanced with structural break analysis for the prediction of MSW generation at the national level. The model was created and tested using the data of 44 countries comprising the Organization for Economic Co-operation and Development (OECD) and 28 member states of the European Union (EU28) as well as some OECD partner countries for the period from 2000 to 2012. With regards to the global economic crisis of 2008 and the structural changes it caused, two different ANN models were compared: one where the structural breaks were neglected and the other in which structural breaks were taken into account.

Materials and methods

Input and output parameters

In order to provide an ANN-based model with accurate predictions, it is very important to identify the parameters that significantly affect the amount of generated waste (Benítez et al. 2008; Gallardo et al. 2014) and to utilize adequate input data.

Different indicators related to economy, demography, industry and environmental phenomena, as well as to social and consumer habits were used as initial input variables. Most of these parameters were previously used for MSW generation modelling like GDP (Intharathirat et al. 2015; Antanasijević et al. 2013a; Daskalopoulos et al. 1998; Chung 2010; Rimaityte et al. 2012), DMC (Antanasijević et al. 2013a), share of urban population (Bandara et al. 2007; Lebersorger and Beigl 2011; Keser et al. 2012; Intharathirat et al. 2015), population density (Benítez et al. 2008; Lebersorger and Beigl 2011; Keser et al. 2012; Gallardo et al. 2014; Intharathirat et al. 2015), household size (Dyson and Chang 2005; Lebersorger and Beigl 2011; Keser et al. 2012; Intharathirat et al. 2015), unemployment rate (Rimaityte et al. 2012; Keser et al. 2012; Intharathirat et al. 2015), etc. The list of input parameters and their descriptive statistics for the period 2000–2012 are presented in Table 1.

Domestic material consumption (DMC), presented in Table 1, measures the total amount of materials directly used in the economy, excluding hidden flows (UN 2003). Value added of industry refers to the contribution of industry to overall GDP. Inbound tourism expenditure includes expenditure of non-resident visitors. The population within the age group 20 to 65 is the share in total population of people in that age group on 1st January of the current year. Unemployment rate is expressed as the share of total working-age population. Alcohol consumption among the population with an age of 15 years and more is expressed by litres per capita and per year. Carbon dioxide (CO_2) emissions from residential buildings and commercial and public services contain all emissions from fuel combustion in households and they are given in Table 1 as the share of total fuel combustion.

This study includes 44 countries; thereof, 34 are OECD member countries, 28 countries are EU members (EU28) and 3 of them are additional OECD partner countries. Seven of EU28 countries are not OECD members, four OECD countries from Europe are not members of European Union and nine of OECD countries are non-European (Fig. 1, Table 2). The data for 44 observed countries were mainly collected from the following databases: OECD Statistics (OECD 2015a), Eurostat—European Statistical Office (European Commission 2015), World Bank (World Bank 2015) and United Nation Department of Economic and Social Affairs (UN 2015).

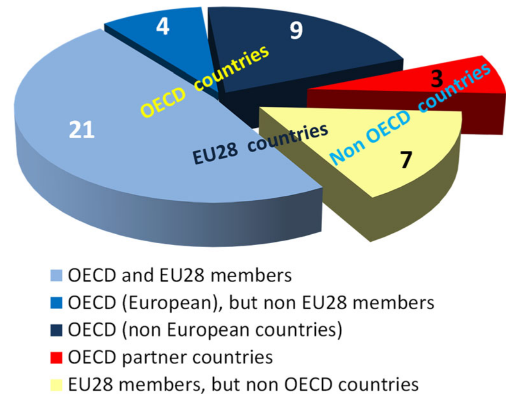

Fig. 1 Structure of the countries represented in the study

About 57 % of the observed population and about 49 % of surface area of the 44 countries covered by this study belongs to OECD partner countries (Brazil, China and Russia), while about 17 % of population and nearly 6 % of the total surface area belongs to the EU28 countries.

The 44 selected countries are very different in the terms of the size of their territory, population and economic and industrial development, on one hand, and also in terms of their social and cultural habits, on the other. Additionally, the generation of municipal solid waste can be affected by climatic conditions that vary significantly

Table 1 Descriptive statistics of inputs selected for modelling of MSW generation

Input variable	Unit	Mean	St. dev.	Min	Max
Gross domestic product (GDP)	curr. US$ pc[a]	0.87	0.41	0.11	2.52
Domestic material consumption (DMC)	t pc[b]	19.18	9.68	6.77	54.74
Urban population (UP)	-[c]	0.75	0.12	0.36	0.98
Population density (PD)	p/km^2[d]	145	211	2.5	1354
Average household size (ASH)	p ph[e]	2.70	0.47	2.00	4.25
Industry, value added (IND)	-[c]	0.23	0.06	0.07	0.42
Tourism expenditure in the country (TUR)	US$ pc	1027	1335	10.5	9991
Population by age group 20–65 (POP)	-[c]	0.61	0.03	0.51	0.70
Unemployment rates (UNR)	-[c]	0.08	0.04	0.02	0.23
Alcohol consumption (pop. aged 15 and over; ALC)	l pc[f]	9.40	2.80	1.20	15.30
Household final consumption expenditure (HFCE)	curr. US$ pc	1.50	3.02	0.001	17.02
CO_2 emissions from residential buildings and com. and public services (CO_2)	-[c]	0.16	0.07	0.004	0.39

[a] Current US dollar per capita

[b] t pc—tonnes per capita

[c] Share of total

[d] Persons per square kilometer

[e] Persons per household

[f] Litres per capita

Table 2 Descriptive statistics of MSW generation (kilograms per capita)

Country/association	Mean	Stand. dev.	Minimum	Maximum
Belgium (BE)[a]	474	14	450	494
Bulgaria (BG)[b]	573	45	460	612
Czech Republic (CZ)[a]	300	19	274	335
Denmark (DK)[a]	672	63	598	789
Germany (DE)[a]	602	26	564	642
Estonia (EE)[a]	383	60	280	453
Ireland (IE)[a]	688	67	587	792
Greece (GR)[a]	453	38	407	531
Spain (ES)[a]	577	63	468	658
France (FR)[a]	530	11	506	543
Croatia (HR)[b]	342	63	245	415
Italy (IT)[a]	535	18	504	559
Cyprus (CY)[b]	683	29	628	729
Latvia (LV)[b]	328	30	271	391
Lithuania (LT)[b]	402	26	365	445
Luxembourg (LU)[a]	672	16	646	697
Hungary (HU)[a]	441	28	382	468
Malta (MT)[b]	602	44	540	674
Netherlands (NL)[a]	589	17	549	606
Austria (AT)[a]	586	15	562	608
Poland (PL)[a]	304	25	256	322
Portugal (PT)[a]	472	29	441	520
Romania (RO)[b]	354	45	268	411
Slovenia (SL)[a]	475	56	362	542
Slovakia(SK)[a]	286	25	239	319
Finland (FI)[a]	486	20	458	521
Sweden (SE)[a]	465	20	428	493
United Kingdom (UK)[a]	556	43	477	602
Iceland (IS)[c]	449	89	306	563
Norway (NO)[3]	457	63	361	613
Switzerland (CH)[c]	687	26	656	736
Turkey (TR)[c]	427	19	400	454
Australia (AU)[d]	566	75	448	690
Brazil (BR)[e]	301	25	272	336
Canada (CA)[d]	761	31	710	811
Chile (CL)[d]	360	19	329	385
China(CN)[e]	258	19	230	286
Israel (IL)[d]	598	19	558	631
Japan (JP)[d]	400	27	354	432
Republic of Korea (KR)[d]	373	10	358	388
Mexico (MX)[d]	331	18	305	360
New Zealand (NZ)[d]	696	92	559	779
Russian Federation (RU)[e]	429	61	350	563
United States (US)[d]	760	24	723	787

[a] EU28 and OECD member country

[b] EU28, but not OECD member country

[c] European OECD member, but not EU28 member country

[d] Non European OECD member country

[e] OECD partner country

between the countries covered in this research (Gómez et al. 2009; Keser et al. 2012; Denafas et al. 2014). All these complicate the creation of a unique prediction model for all of the observed countries.

Annual quantities of generated municipal solid waste in kilograms per capita at the national level were used as the single output variable in this research. This data was obtained from OECD Environment Statistics (OECD 2015b), Eurostat—European Statistical Office (European Environment Agency 2014) and from national data bases in cases where the data was not available in the two abovementioned sources. Statistics of municipal solid waste generation at the national level and for the entire MSW dataset are shown in Table 2.

The dataset is organized as a panel data form, which combines characteristics of both time series and cross-section data. Time series is a set of observations on the values that a variable has at different times, while cross-section data is data coming from one or more variables collected at the same point in time. Panel or longitudinal data is a special type of data in which the same cross-sectional unit is surveyed over time. In short, panel data has space as well as time dimensions (Gujarati and Porter 2009).

In addition, this dataset represents a so-called balanced panel, which means that each subject (country) has the same number of observations. The panel contains data for 12 different independent and 1 dependent variables for 44 countries during the period spanning 13 years (from 2000 to 2012). The dataset was divided into three subsets: the first two were used for training and validation of the ANN model (in proportion 4:1), while the third one (test subset) was used to test the model prediction capability.

Artificial neural networks

Artificial neural networks (ANNs) are mathematical tools inspired by biological neural networks. The development of ANNs derives from the desire to construct artificial systems capable of sophisticated "smart" calculation, in a similar way as the human brain routinely performs (Freeman and Skapura 1991).

An artificial neuron receives input signals analogue to electrochemical impulses and responds with adequate output, which to a certain extent corresponds to the output of biological neurons. An ANN consists of neurons grouped into layers (input, hidden and output layer) whereby an ANN can have one or more hidden layers. In most cases, one hidden layer is sufficient for an ANN to approximate any nonlinear function (Noori et al. 2010).

In this study, a general regression neural network (GRNN; Specht 1991) was used, since it proved to be superior to back propagation (BP) ANN for the forecasting of municipal waste generation at the national level (Antanasijević et al. 2013a). GRNN architecture consists of four layers, where the number of neurons in the input layer corresponds to the number of input variables, while the number of neurons in output layer is equal to number of output variables. The number of pattern neurons corresponds to the number of data patterns, and the number of neurons in the summation sublayer is consistently higher by one when compared to the number of output neurons. Since there is one output neuron in this case, there are two neurons in the summation sublayer, one being the summation neuron and other division neuron (Fig. 2).

A GRNN learning algorithm can be regarded as a type of Nadaraya–Watson kernel regression (Tomandl and Schober 2001). The regression of a dependent variable *y*, which is usually a vector and represents the system output, on an independent variable *x* (usually also a vector and the system input) is, in fact, the computation of the most probable value of *y*. The determination of the *y* value for a known *x* value requires the assumption of a functional dependency with unknown parameters. In the GRNN algorithm, this functional dependency is expressed in terms of a probability distribution function $f(x,y)$, whose determination is based on the *x* value using Parzen window estimation (Specht 1991).

Considering that the distribution function $f(x,y)$ is not known, it needs to be calculated using the known values of variables *x* and *y*. Within this calculation, the prediction of the unknown value *y* is actually performed on the basis of probability whose range (width) depends on a parameter known as the smoothing factor (σ_f), which is determined for every couple of *Y* and *X*. *X* is a particular (e.g. measured) value of random variable *x*, and the correlated *Y* is a particular value of the random variable *y* (Tomandl and Schober 2001). The final probability is equal to the sum of these individual probabilities.

The smoothing factor represents the width of Gaussian curve for every individual probability density function and it is the only parameter that is unknown in the GRNN algorithm. In general, the smoothing factor is always greater than 0, and the closer it gets to zero, the regression surfaces are smoother. In this study, genetic algorithm was used for the determination of smoothing factor; more details on this approach can be found in (Kim and Kim 2008; Chen and Chang 2009).

In practice, the GRNN compares the distances between the input data (vectors) and predicted values using the following equation:

$$Y(X) = \frac{\sum_{i=1}^{n} Y_i exp\left(\frac{-D_i^2}{2\sigma_f^2}\right)}{\sum_{i=1}^{n} exp\left(\frac{-D_i^2}{2\sigma_f^2}\right)} \quad (1)$$

$Y(X)$ is a value obtained by the GRNN for input X. Y_i is a measured (accurate) value and D_i is the distances of training patterns in *N*-dimensional space, i.e. Euclidean distance.

The numerator in Eq. 1 is the summation neuron which computes the sum of weighted outputs of the pattern layer, while the denominator is the division neuron which calculates the unweighted outputs of the pattern neurons. In order to get the desired estimate, the output layer divides the output of the summation neuron by the output of the division neuron (Antanasijević et al. 2014).

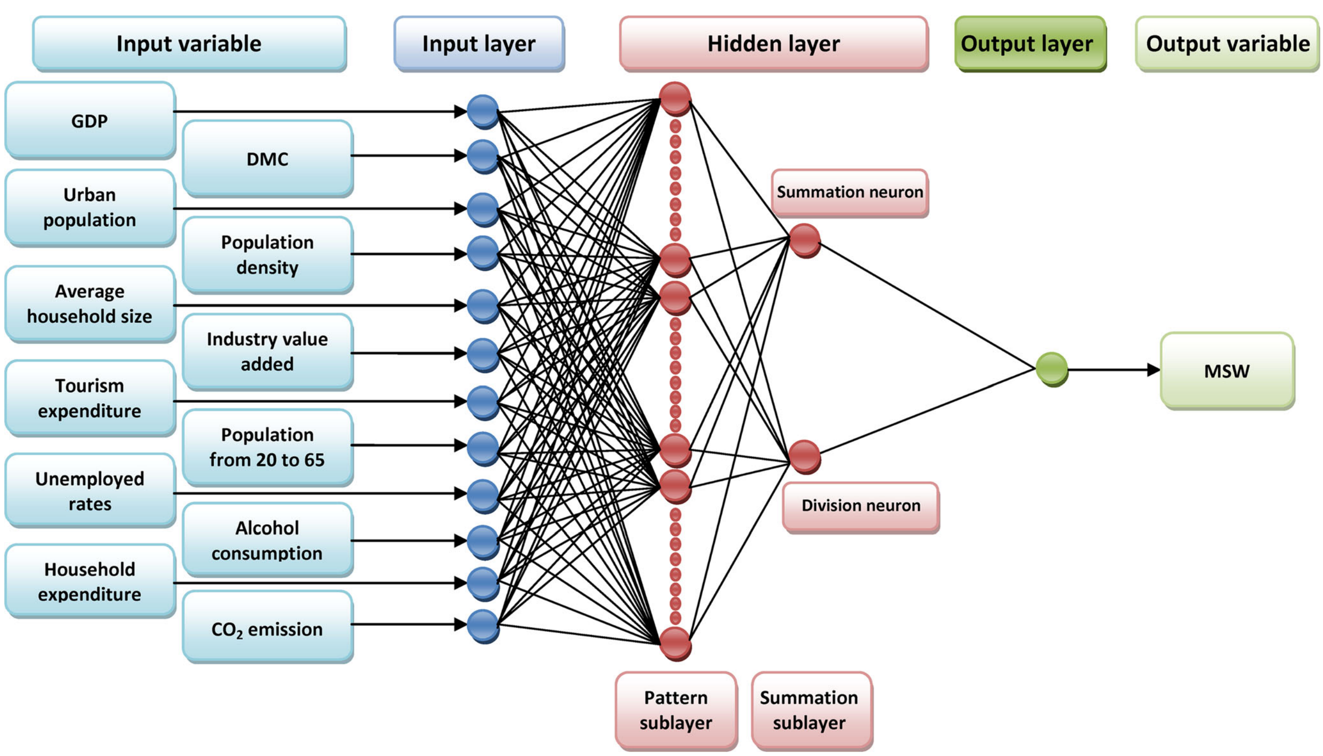

Fig. 2 GRNN architecture used for forecasting of MSW generation on national level

Structural breaks

Major events at the financial market (such as global or regional financial crisis), commodity market (e.g. large fluctuations in the oil price) or in the legislation field (e.g. adoption and implementation of some crucial laws), may cause abrupt changes in the economic and social environment (Greene 2012) called structural breaks. In that scenario, it can be expected that the economy demonstrates different features and performance in the periods before and after structural breaks. If a structural break exists, neglecting this phenomenon can lead to significant errors in the modelling of economy parameters.

One such event is the 2007–2009 financial crisis that began in 2007 and continued to seriously affect the world economy up until the present day (Dwyer and Lothian 2012). Considering the occurrence of the global economic crisis, the presence of a structural break in the studied period (2000–2012) is therefore to be expected. To test this hypothesis, the panel dataset was divided by countries into 44 individual time series, one for each country.

Tests of structural breaks can generally be classified into two groups: tests based on the assumption that the break date is known and tests that examine the presence of structural break at an unknown place within the sample. Most of the tests estimate whether a structural break is present by using the null hypothesis of no structural change, against the alternative of break at time τ (Perron 2006).

Chow test is most commonly used to test for the presence of structural break in a time series when the break date is known (Wooldridge 2013). For a regression model:

$$y_t = \beta_0 + \beta_1 x_t + u_t, for\ all\ t = 1, 2, \dots T \tag{2}$$

the sum of squared residuals is:

$$SSR_R = \sum\nolimits_{t=0}^{T} u_t^2 \tag{3}$$

But, if there is a structural break at the time τ in the regression model (Eq. 2), sample can be split around the break point to:

$$y_{1t} = \beta_{10} + \beta_{11} x_{1t} + u_{1t}, t = 1, 2, \dots \tau \tag{4}$$

and

$$y_{2t} = \beta_{20} + \beta_{21} x_{2t} + u_{2t}, t = \tau + 1, \dots T \tag{5}$$

The individual sum of squared residuals is:

$$SSR_1 = \sum\nolimits_{t=0}^{\tau} u_{1t}^2 \text{ and } SSR_2 = \sum\nolimits_{t=\tau+1}^{T} u_{2t}^2 \tag{6}$$

The total sum of squared residuals from the equation (6) is:

$$SSR_{UR} = SSR_1 + SSR_2 \tag{7}$$

The sum of squared residuals SSR_R (Eq. 3) from the pooled estimation (Eq. 2) is the restricted sum of squared residuals because it is obtained by imposing the restrictions that $\beta_{10} = \beta_{20}$ and $\beta_{11} = \beta_{21}$, so there is only one regression model (Eq. 2). On the other hand, the sum of squared residuals SSR_{UR} (Eq. 7) for the two separately estimated time periods (Eq. 4 and 5) is an unrestricted sum of squared residuals.

The Chow test is based on the Wald statistic and it is given as the F statistic which represents the comparison of the restricted and unrestricted sum of squared residuals. A single breakpoint can be computed as (Gujarati and Porter 2009):

$$F = \frac{(SSR_R - SSR_{UR})/k}{(SSR_{UR})/(T-2k)} \tag{8}$$

where T is the total number of observations and k is the number of parameters in the observed equation.

The null hypothesis of the test is that there is no break at the specified breakpoints. In that case, $\beta_{10} = \beta_{20}$ and $\beta_{11} = \beta_{21}$, which implies that Eq. 2 can be used. But if F from Eq.8 is greater than the upper critical value of the F distribution, with a significance level of less than 5 %, then structural change cannot be ignored.

Besides the Chow test, the Quandt–Andrews test has also been applied in this study for finding unknown structural breakpoints in the sample. The basic idea of this test is that a single Chow test is performed at every observation over the interval $[\xi T, (1 - \xi)T]$, and after that, all of the n test statistics from those tests are summarized and the supremum of the F statistics is calculated (Berger 2011):

$$\sup F = \sup \tau \epsilon [\xi T, (1-\xi)T] F \tag{9}$$

Two additional test statistics, the average and exponential F statistics, have been developed (Andrews and Ploberger 1994):

$$Ave\ F = \frac{1}{n} \sum\nolimits_{\tau=\xi T}^{(1-\xi)T} F(\tau) \tag{10}$$

$$Exp\ F = \ln\left[\frac{1}{n} \sum\nolimits_{\tau=\xi T}^{(1-\xi)T} \exp\left(\frac{1}{2} F(\tau)\right)\right] \tag{11}$$

The trimming parameter (ξ) is used because the distribution of statistics (Eq.9–11) becomes degenerated as it approaches the beginning (ξT) or the end $[(1 - \xi)T]$ of the sample. Because of that, it is generally suggested that the first ξT and last ξT of the observations are not to be included into the testing procedure. Like in the Chow test, with the Quandt–Andrews test, the null hypothesis of no break is rejected if the maximum of the F statistic is greater than critical values.

Performance metrics

The characteristics of models and their ability to provide accurate results in this study were determined using the following criteria:

The root mean squared error (RMSE):

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\left[\sum\nolimits_{i=1}^{n}(P_i - O_i)^2\right]} \quad (12)$$

The mean absolute error (MAE):

$$MAE = \frac{1}{n}\sum\nolimits_{i=1}^{n}|P_i - O_i| \quad (13)$$

The mean absolute percentage error (MAPE):

$$\mathrm{MAPE} = \frac{1}{n}\sum\nolimits_{i=1}^{n}\frac{|P_i - O_i|}{O_i}\cdot 100 \quad (14)$$

Percentage of prediction within a factor 1.1 (FA1.1) of observed values:

$$0.9 < \frac{P_i}{O_i} < 1.1 \quad (15)$$

Modified index of agreement (d_1):

$$d_1 = 1 - \frac{\sum\nolimits_{i=1}^{n}|P_i - O_i|}{\sum\nolimits_{i=1}^{n}\left(\left|P_i - O_i\right| + \left|O_i - O_i\right|\right)} \quad (16)$$

The Nash–Sutcliffe coefficient of efficiency (E_f):

$$E_f = 1 - \frac{\sum\nolimits_{i=1}^{n}(P_i - O_i)^2}{\sum\nolimits_{i=1}^{n}\left(P_i - O_i\right)^2} \quad (17)$$

In Eq. 12–17, n is the number of predictions, P_i is predicted and O_i is the observed value of MSW generation.

FA1.1 shows the proportion of predictions with an error of less than ±10 %, i.e. the percentage of cases in which the values of the ratio among predicted and observed values are in the range of 0.9 to 1.1. d_1 is introduced by (Legates and McCabe Jr 1999), and the advantage of this form of Willmott's index of agreement is that the errors and differences are given their appropriate weighting. The Nash–Sutcliffe coefficients of efficiency range from −∞ to 1, where E = 0 means that the model is not performing better than by merely taking the mean value as predicted output (Wang et al. 2015; Duveiller et al. 2016).

Results and discussion

Correlation analysis

Besides the selection of representative independent input variables for a particular dependent output variable, the performance of ANN model may be strongly affected by a potential correlation among independent variables. If correlated input data are used, then this can cause confusion to the neural network during the learning process. For this reason, if two variables are highly correlated, one of them can be removed from the dataset without adversely affecting the ANN performance (Walczak and Cerpa 1999) or even with an increase of model performance (Antanasijević et al. 2013b).

In this study, after the data was collected, a correlation analysis was carried out, the primary objective thereof being to measure the strength or degree of linear association between two variables (Gujarati and Porter 2009). To examine the relationship between input variables, Pearson correlation coefficients were used. A correlation coefficient greater than 0.8 is interpreted as high (Hamilton 1990) and variables in that case are highly correlated. For this reason, if there are input variables with the mutual correlation coefficient greater than 0.8,

Table 3 Correlation analysis results

	GDP	DMC	UP	PD	AHS	IND	TUR	POP	UNR	ALC	HFCE
GDP	1.00										
DMC	0.28	1.00									
UP	0.44	0.19	1.00								
PD	0.05	−0.34	0.30	1.00							
AHS	−0.55	−0.10	−0.16	−0.01	1.00						
IND	−0.38	0.01	−0.36	−0.16	0.22	1.00					
TUR	0.63	0.15	0.21	0.17	−0.21	−0.52	1.00				
POP	−0.02	−0.05	−0.43	0.12	−0.35	0.12	0.11	1.00			
UNR	−0.40	−0.21	−0.25	−0.13	0.08	−0.09	−0.20	0.18	1.00		
ALC	0.21	0.16	−0.20	−0.11	−0.57	−0.17	0.22	0.53	0.10	1.00	
HFCE	0.27	−0.19	0.10	0.15	−0.27	0.07	−0.12	0.00	−0.23	−0.07	1.00
CO2	0.28	−0.24	−0.17	0.04	−0.23	−0.06	0.04	0.19	−0.01	0.33	0.19

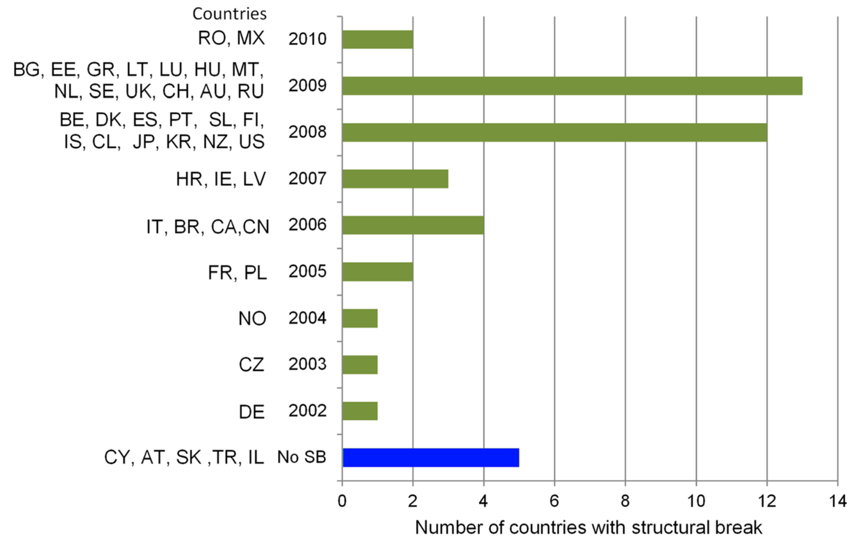

Fig. 3 Occurrence of structural break in time series for each country

one of these variables can be removed. The conducted correlation analysis showed that there were no variables with a mutual coefficient of correlation higher than 0.8 (Table 3).

Testing structural breaks

In this study, it was necessary to examine whether and when there was an occurrence of structural changes in the observed countries. To test the presence of structural breaks for each country, the Quandt–Andrews test was conducted first. After that, for every single year after the year when a structural break occurred, the Chow test was applied to check whether there were any additional structural changes after the appearance of the dominant structural break.

By applying the Chow test and Quandt–Andrews tests for each of the individual countries, it can be concluded that for the most of the countries, there was a statistically significant structural break which occurred as a consequence of the 2007–2009 global financial crisis (Fig.3).

As can be seen from Fig.3, statistically significant structural breaks as a result of the global financial crisis (period from 2007 to 2010) have occurred in 68.2 % of all observed countries. In the previous years (2002–2006), structural changes have occurred in 20.4 % of the sample. The reasons for the occurrences of structural breaks in that period may be different, for instance, a recession in 2002 in Germany (Dustmann et al. 2014) or the changed scope of MSW to include only household waste in 2004 in Norway (ETC/SCP 2013a). There were no significant structural changes in five countries which contributes 11.4 % of all observed countries.

It should be noted that structural changes in economy were not always accompanied by simultaneous changes in waste generation. For this reason, structural breaks were lacking in some countries (Cyprus, Austria, Slovakia, Turkey and Israel) in the observed period.

The prediction of MSW generation

Considering the results of structural break testing, two models were created: a GRNN model, in which structural breaks were neglected, and SB-GRNN model, which took into account structural breaks. In the GRNN model, the data from the years 2000–2010 were used for training and validation (484 data patterns), while the data from the years 2011–2012 were used to test the model (Table 4). The data from 2000 to 2010 was randomly divided into training and validation subsets at a ratio of about 4:1, respectively. In the SB-GRNN model, only the data from the years after the structural breaks (if they occurred) until 2011 was used for training and validation, while the data from 2012 were used to test the SB-GRNN model. It

Table 4 Number of data patterns per dataset and corresponding subsets

Dataset	GRNN	SB-GRNN
Data used for model development	2000–2010 data (484 patterns)	SB-2011 data (192 patterns)
	Training subset, 388 patterns	Training subset, 154 patterns
	Validation subset, 92 patterns	Validation subset, 38 patterns
Data used for model evaluation	2011–2012 data	2012 data
	Test subset, 88 patterns	Test subset, 44 patterns
Ratio between development and evaluation data	5.5	4.4

Table 5 Performance metrics of created MSW models (test dataset)

Metric	Unit	GRNN		SB-GRNN
		overall	for 2012	
r		0.956	0.944	0.981
d_1		0.871	0.851	0.925
E_f		0.909	0.879	0.962
MAE	kg pc	29.9	34.6	17
RMSE	kg pc	41.7	47.7	26.4
MAPE	%	6.7	8.0	4.0
FA1.1	%	80.7	79.5	86.4

can be observed that the SB-GRNN model was tested with 50 % data points less, and this reduction was needed in order to maintain the ratio between the data used for model development and the data used for evaluation above 4 (Table 4).

Although both models (Table 5) demonstrated good performance, better predictions were achieved with the SB-GRNN model, which had MAPE = 4.0 % and FA1.1 = 86.4 %. Since GRNN model had MAPE = 6.7 % and FA1.1 = 80.7 %, the selection of data based on SB analysis apparently resulted in an improvement of the MSW model.

The results obtained for the test data using the GRNN and SB-GRNN models are presented in Fig. 4. It can be seen that SB-GRNN has enhanced prediction capability (R^2 = 0.96, d_1 = 0.925, E_f = 0.962) in comparison with the GRNN model (R^2 = 0.91, d_1 = 0.871, E_f = 0.909). Further performance analysis can be made by accessing the discrepancy ratio (Fig. 4.): the GRNN model has about 80 and 95 % predictions that are within the error margin of ±10 and ±20 %,

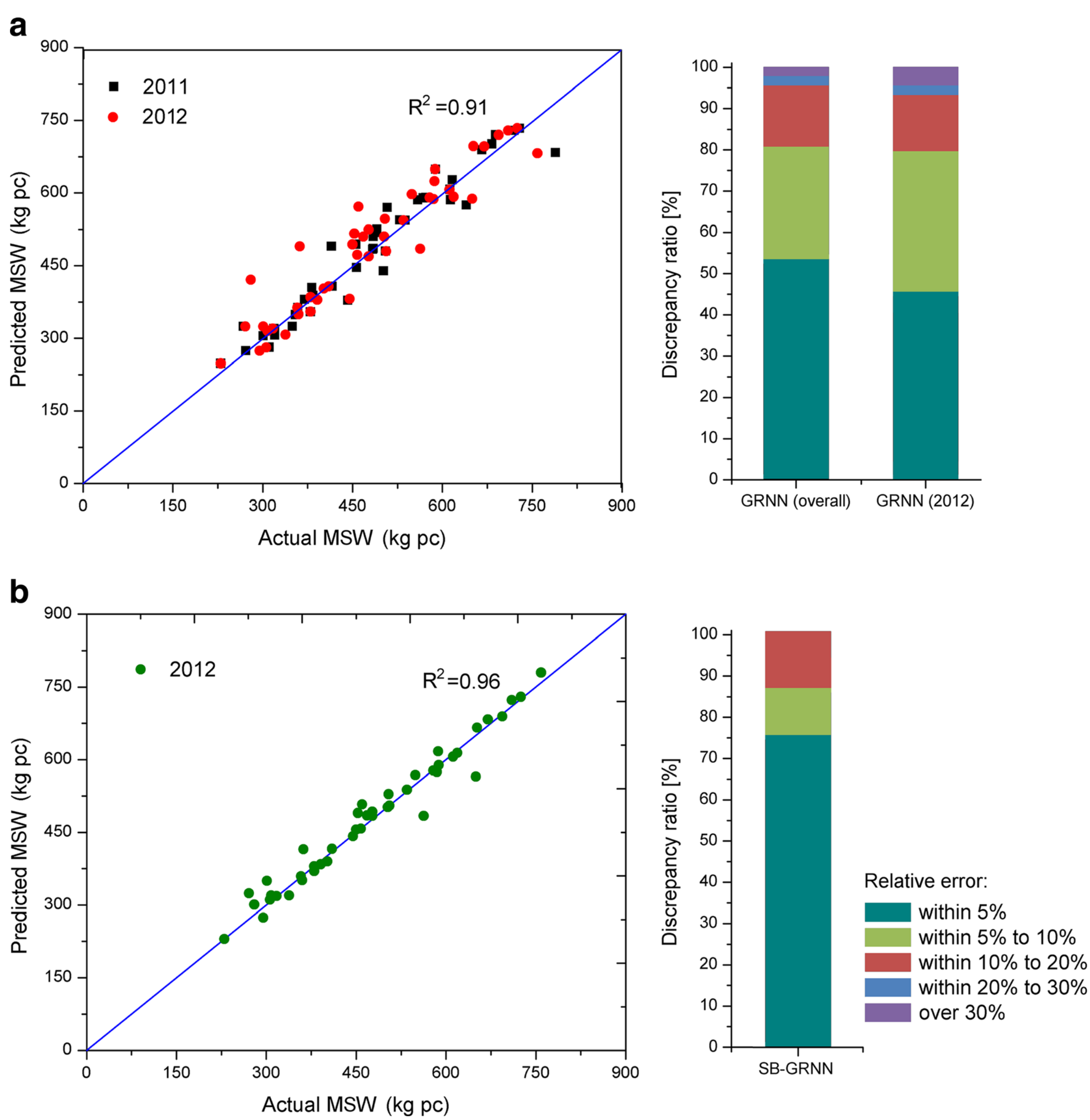

Fig. 4 Actual vs. predicted MSW generation with corresponding discrepancy ratios: **a** GRNN model and **b** SB-GRNN model

respectively, while SB-GRNN achieves 86 and 100 % within the same error margins. Moreover, the ratio of MSW predictions with the relative error up to ±5 % significantly increased as a result of taking SB into account from 54 to 75 %, which yield an SB-GRNN MAPE value of only 4.0 %.

As can be observed in Table 5 and Fig. 4, the superior performance of SB-GRNN over the simple GRNN model is even more obvious, if only the results for 2012 are analysed.

Comparisons of the relative errors for the test data are presented in Fig. 5. Relatively higher errors (≥15 %) for the SB-GRNN model can be observed only for Romania, Latvia and Slovenia, but it appears that the deviation between the actual and predicted values for those countries can be attributed to the uncertainty of MSW data used for the training and testing of the model.

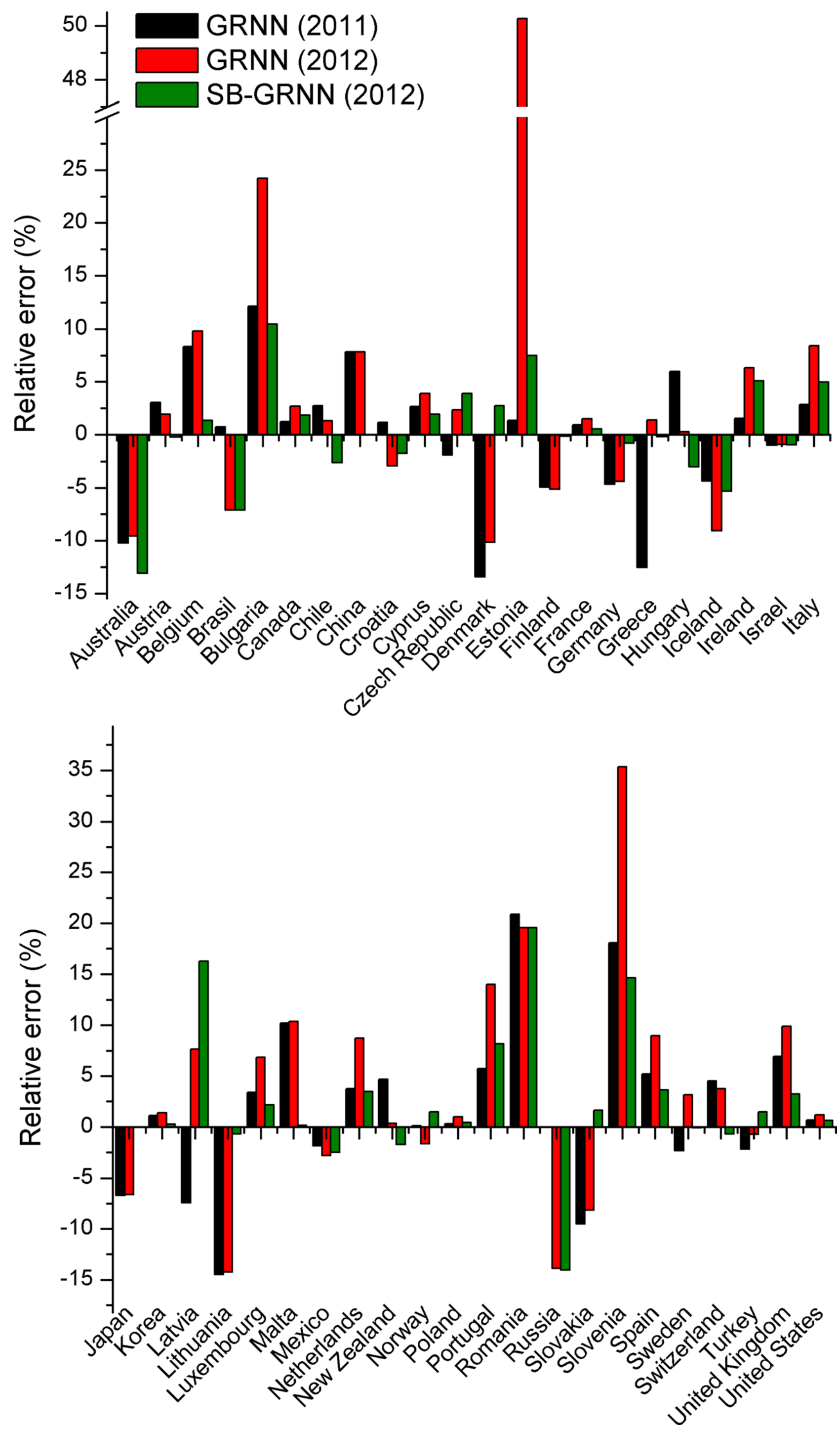

Fig. 5 Comparison of GRNN and SB-GRNN based on relative errors for the test data

The highest relative error was obtained for Romania (≈20 %), for which the actual MSW values are estimated, not measured (Eurostat 2015), because waste collection services were not covering the entire population, favouring illegal dumping (Mihail 2013). Therefore, those values have increased uncertainty; it can be noticed that both models provided MSW predictions for Romania with similarly high relative errors. In the case of Latvia, the SB-GRNN model overestimated the MSW quantity, which can be related to the fact that significant amounts of municipal waste (e.g. metals and glass packaging) are exported for recovery in other countries, and therefore, this waste has not been included in the amounts that Latvia has reported to Eurostat as MSW (ETC/ECP 2013; Kara 2014). For Slovenia, The Statistical Office of the Republic of Slovenia used the methodology for collecting data on generated MSW which includes waste imported for recycling, but excludes exported waste. Also, package waste was not always reported as MSW, which can be another source of uncertainty (ETC/SCP 2013b).

Conclusion

This paper describes development of a new model for forecasting the generation of MSW at the national level. The model based on general regression neural networks was applied to 44 countries of differing size, population, level of economic development, social patterns, climates and other factors.

An additional objective of this research was to examine a potential influence of structural breaks (SBs), abrupt changes in economy and society, to MSW generation, especially having in mind the financial crisis between 2007 and 2009 which still bears consequences to the global economy. Two models were created for that purpose: in the first model, a GRNN, the existence of SBs was neglected, whilst in the other model, a SB-GRNN, took into account potential SBs for each individual country and then only input variables from the years after the occurrence of SBs were used for modelling. The input dataset comprised 12 different variables obtained from official databases.

While both models achieved good results, the SB-GRNN model demonstrated superior performance, with relative errors in the range of ±10 % (FA1.1) for 86 % of countries, FA1.2 achieving 100 %, a mean absolute percentage error (MAPE) of 4.0 % and R^2 = 0.96, in comparison with the GRNN model results (FA1.1 = 81 %, MAPE = 6.7 % and R^2 = 0.91).

Based on the presented results, it can be concluded that the application of analysis of SBs can further enhance the forecasting capabilities of general regression neural networks models and that the enhanced model has a potential to provide accurate predictions of MSW generation for a wide spectrum of countries, different in the terms of size, population, level of industrial and economic development, as well as social and climatic factors. In addition, since the model uses widely available statistical parameters as inputs, its application may contribute to overcome the lack of data for municipal solid waste generation, which is frequently a challenge in developing countries. Further research should demonstrate whether the techniques applied in this study, with appropriate adjustments, can provide satisfactory results when applied for the prediction of healthcare waste, waste composition and/or types of waste treatments.

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Compliance with ethical standards

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Statement of human rights and statement on the welfare of animals This article does not contain any studies with human participants or animals performed by any of the authors.

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